Decentralized learning over Wireless Networks with broadcasted-based Subgraph Sampling

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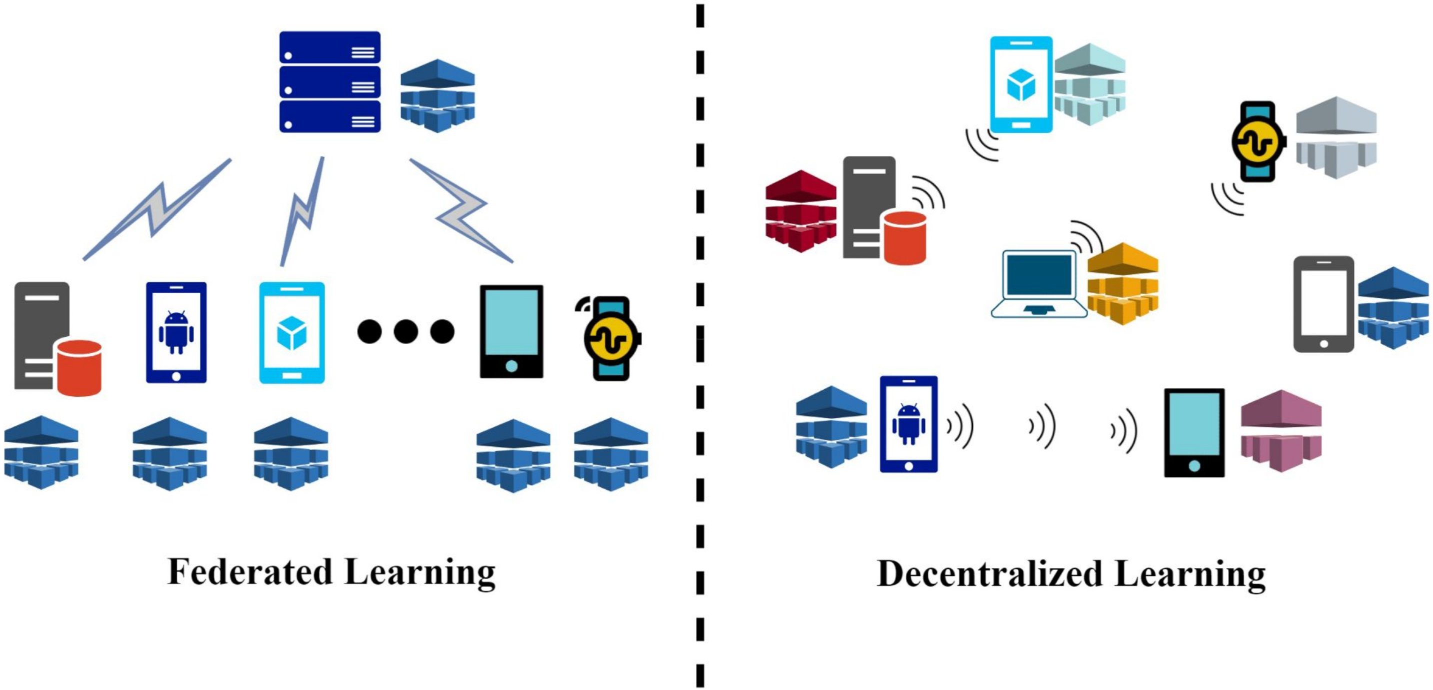
Introduction

Overview of decentralized learning

Decentralized learning involves multiple agents collaboratively training a machine learning model using their local data without sharing the data itself.

Importance:

- Ensures data privacy
- Reduces the need for centralized data storage
- Enhances scalability and robustness in distributed systems



Federated Learning
Decentralized Learning

Objectives of the project

- **Main goal:**

  Duplication of the BASS framework to improve the efficiency of decentralized stochastic gradient descent (D-SGD) in wireless networks.

- **Key challenges addressed:**

  - High communication costs and delays in wireless networks.

  - Issues such as packet collision and access control.

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BASS Framework Overview

Key Innovations

- Broadcast Transmission: nodes can share information with many other nodes at the same time
- Subgraph Sampling: select smaller groups of nodes to send updates at different times
- Symmetric Communication: makes sure that the connections between nodes work both ways

Advantages of BASS

- Improved convergence
- Scalability
- Resilience to Single-Node Failures

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State of the Art

Full Communication in D-SGD

Every node communicates with all other nodes in every iteration.

Drawbacks:

- High communication overhead
- Increased communication delays
- Higher energy consumption

MATCHA

- Balances error convergence and runtime
- Decomposes communication topology into matchings

Comparison with BASS:

- MATCHA reduces runtime with flexible communication budgets
- BASS improves efficiency and reduces delays through broadcast-based communication

Error-runtime Trade-off:
MATCHA achieves faster training times but has higher communication costs compared to BASS

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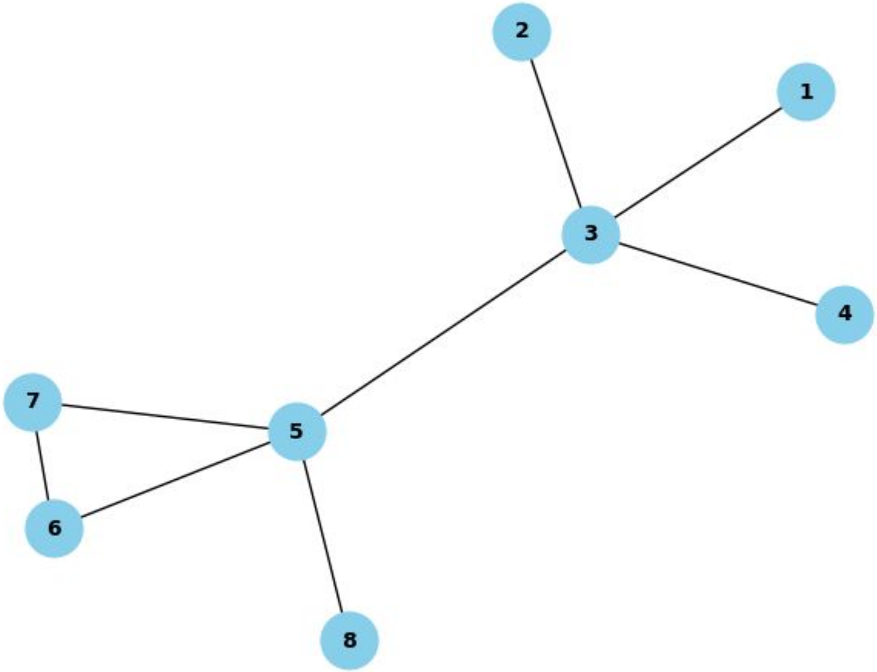
Implementation Details

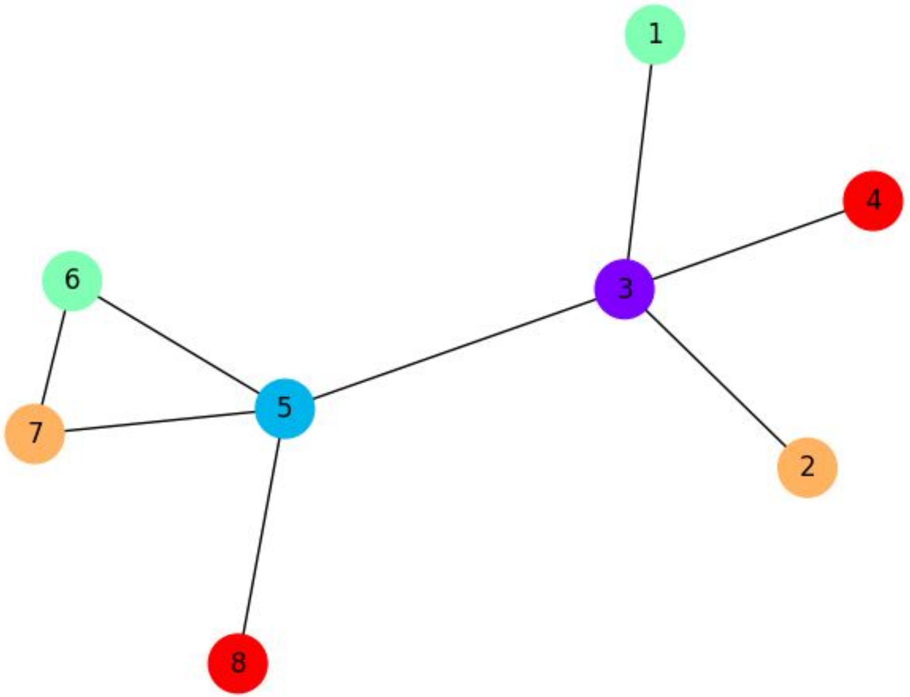
Network Topology



Steps

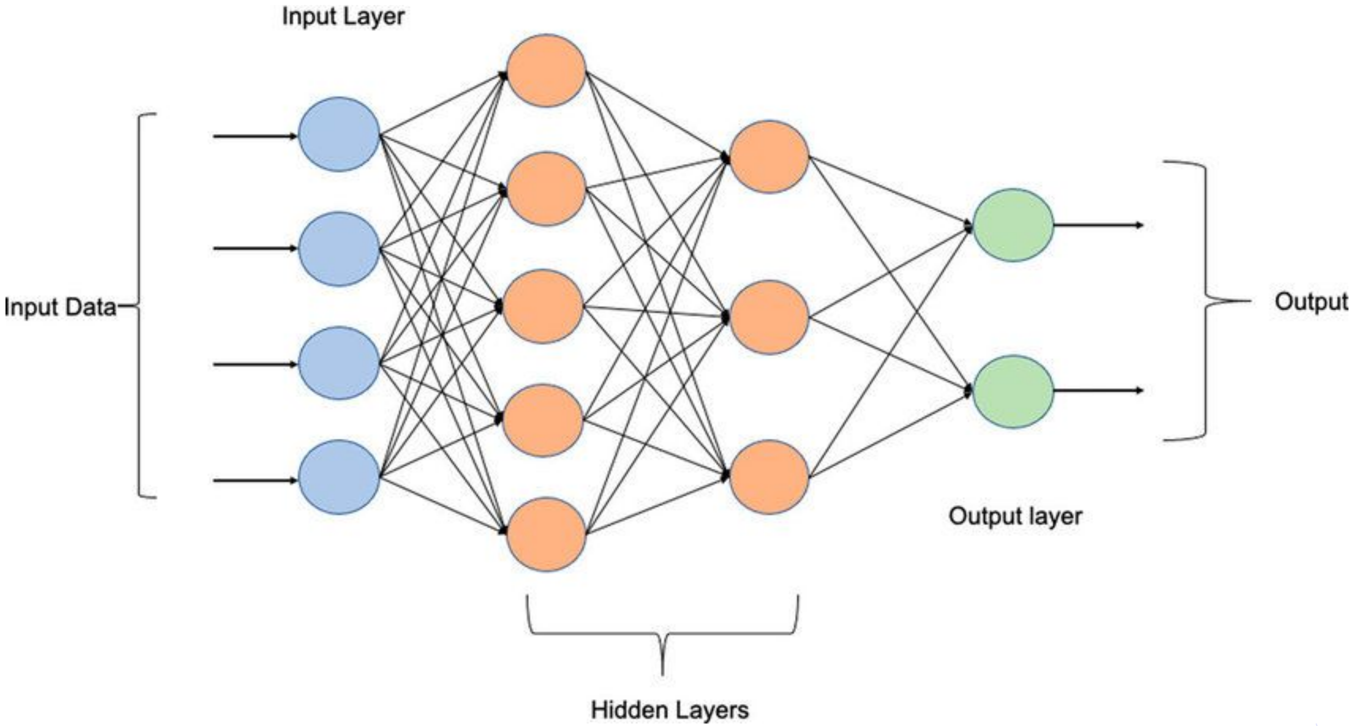
1. Implement base topology
2. Compute betweenness centrality (Node importance)
3. Normalize and assign sampling probabilities
4. Modify Network topology: create auxiliary graph by adding links
5. Apply greedy coloring algorithm: assign colors to nodes in order to create collision-free subsets

Subset division



Subset 0: [3]
Subset 1: [5]
Subset 2: [1, 6]
Subset 3: [2, 7]
Subset 4: [4, 8]

Multilayer Perceptron



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Experiments

Training Setup

- Dataset: MNIST
- Division: Training and testing datasets
- Training Parameters:
  - Number of epochs: 40
  - Loss function: Sparse Categorical Cross Entropy
  - Optimizer: Adam with decaying learning rate
  - Weight decays tested: [0.0001, 0.0005, 0.001, 0.005]

Results:

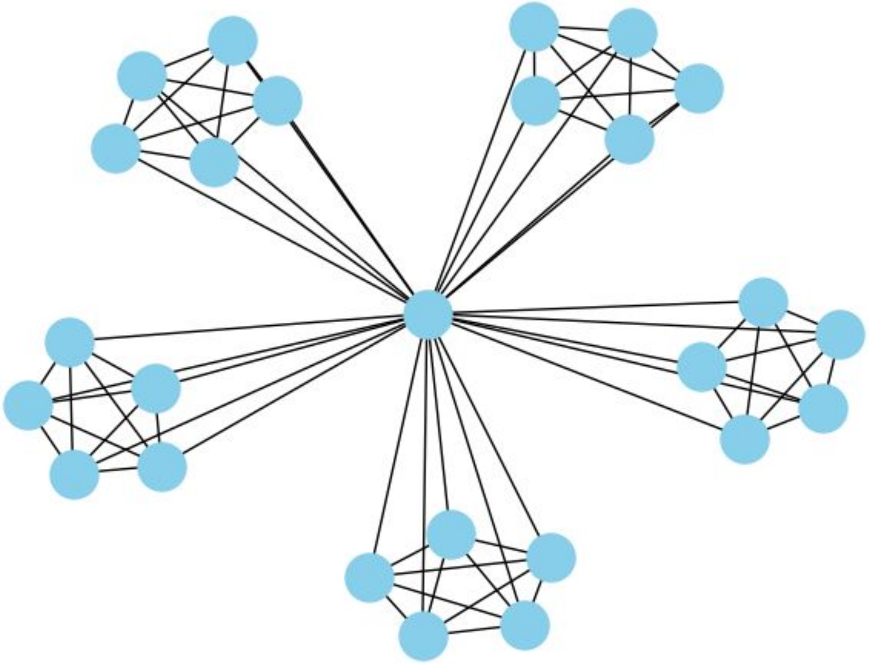
Base topology results:

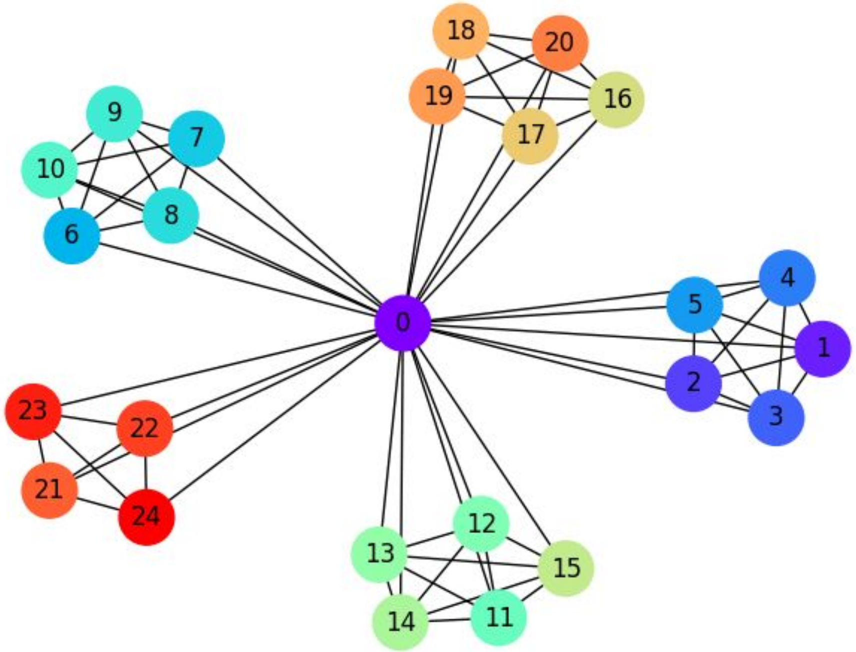
- Test Loss: 0.0741
- Test Accuracy: 99.19%

Topologies compared:

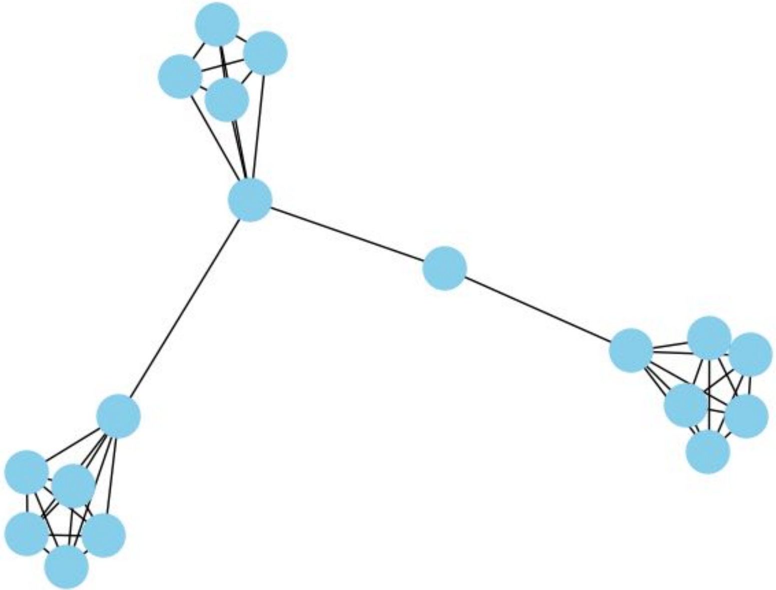
- Star-like (25 nodes)
- Linear (20 nodes)
- Tree-like (15 nodes)

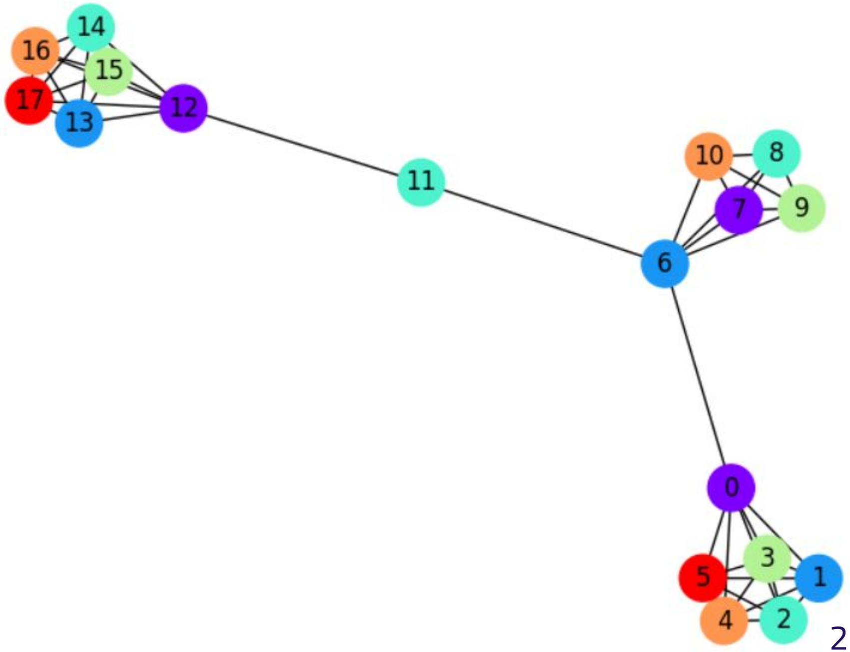
Star topology with N = 25



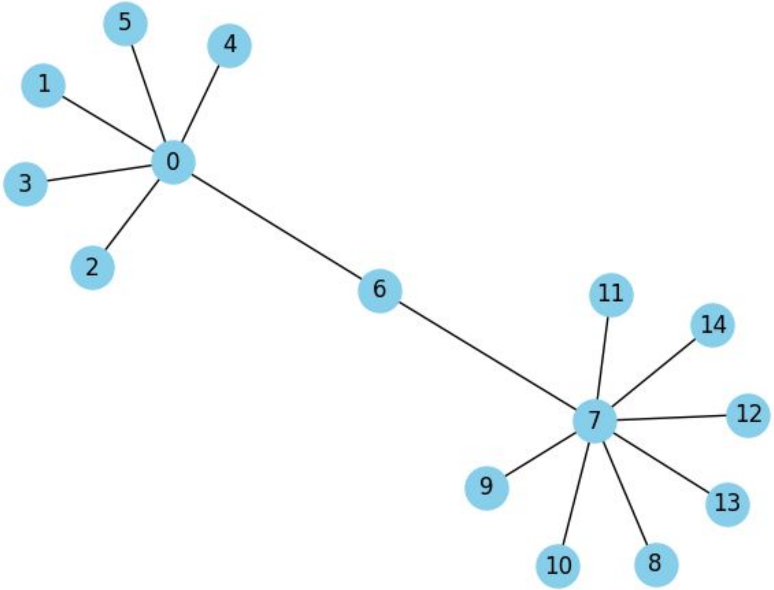


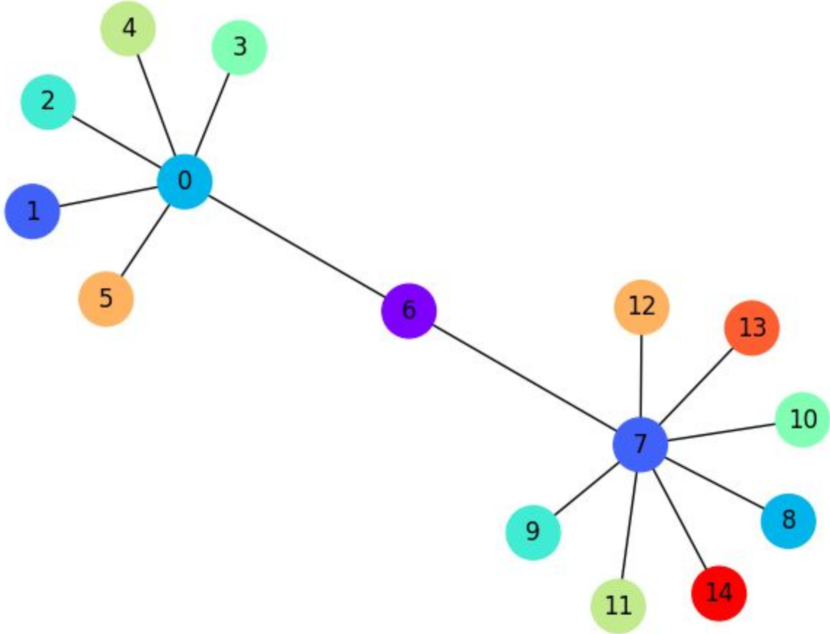
Tree topology with N = 20





Tree topology with N = 15





Results

Graph	Test loss	Accuracy
1	0.1826	96.89%
2	0.1661	97.26%
3	0.1578	97.24%

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Alternative approaches and conclusions

Alternative approaches

Other Node Importance Metrics:

- Eigenvalue Analysis
- Entropy measurement

Alternative Partitioning methods:

- Clustering algorithms (K-means, Spectral clustering)

Conclusion and perspectives

Summary findings:

- Validation of BASS framework
- Efficiency improvements in decentralized learning

Future work:

- Exploration of alternative methods
- Real-world applications

Thank you for your attention!